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Measuring Policy Diffusion with Automated Content Analysis*

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August 25, 2014

Abstract

Policy diffusion means that policy choices in one unit (such as states, cantons, and cities) are influenced by the policy choices of other units. This idea has been studied extensively in several social sciences and, within political science, in subfields such as international relations, American federalism, and public policy. While scholars have demonstrated convincingly that policy diffusion is a real and important phenomenon, much less is known about why and exactly how policies diffuse. We argue that this condition is due to the inherent limitations of existing research designs. This paper puts forward a new approach based on automated frame analysis. Theoretically, the paper focuses on how the perception of policy problems and solutions changes as a result of the adoption of policies elsewhere. We apply this approach to the spread of smoking bans among US states and Swiss cantons. Preliminary results from an analysis of thirteen American newspapers shows that media coverage intensifies when major legislation and illustrates how it prioritizes different consequences of smoking bans, such health, economic fallout for businesses, and enforcement issues.

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1 Introduction

A large number of studies have examined whether and how policies diffuse subnationally or cross-nationally, that is, how the choices of one unit are shaped by the choices of other units (Dobbin, Simmons and Garrett, 2007; Gilardi, 2012; Graham, Shipan and Volden, 2013). The literature has established convincingly that diffusion occurs in a wide range of policy areas. There is strong empirical evidence that policies in one unit are generally influenced by policies in other units. However, the precise nature of this influence remains unclear. There is evidence of some progress in identifying empirically the mechanisms driving diffusion (such as competition, learning, and emulation), but the evidence, while suggestive, is often crude and inconsistent (Maggetti and Gilardi, 2014). A typical research design takes policy adoption or change as the dependent variable and models interdependence, either with spatial econometrics tools (Franzese and Hays, 2007) or within a dyadic framework (Boehmke, 2009; Gilardi and Füglistner, 2008). However, the marginal returns of new studies using conventional research designs are decreasing rapidly. In our opinion, a significant improvement of the state of the art requires new methodological perspectives that allow researchers to unpack policy diffusion processes more effectively.

This paper puts forward a new approach for the study of policy diffusion relying on automated content analysis. Theoretically, it focuses on how the perception of policy problems and solutions changes as a result of the adoption of policies elsewhere. We thereby rely on the concept of frames, namely, patterns of justifications linking specific policies with selective interpretations of their causes and consequences (Entman, 1993; Helbling, Hoeglinger and Wueest, 2010). Empirically, frames can be identified by looking at the words, images, and phrases that are used when conveying information about a policy (Gamson and Modigliani, 1989). In the context of policy diffusion, frames allow us to identify whether policy makers connect a policy with different types of outcomes in relation to the experience of other units. The analysis of the distribution of frames (both across units and over time) will allow us to provide new information about the nature of diffusion processes. Specifically, our approach proceeds in three steps:

1. Description of the variation of frames across units and over time;
2. Analysis of frames as a function of policy adoption in other units;
3. Analysis of policy adoption as a function of frames.

Empirically, we concentrate on smoking bans (that is, policies restricting smoking in public places) in Switzerland and the United States. This choice is motivated by several considerations. First, several American studies (e.g., Shipan and Volden, 2006, 2008; Pacheco, 2012), as well as abundant anecdotal evidence regarding Switzerland,¹ indicate that, in all likelihood, smoking bans have been subject to a diffusion process. This allows us to concentrate on the nature of the process instead of its mere existence. Second, within each country, smoking bans have been adopted in a convenient time frame (about ten years), which is long enough to detect variations and to supply sufficient information but short enough to be practically manageable. Third, the policy has well-defined characteristics and is comparable across units. Fourth, there was significant uncertainty on the consequences of the policies with respect to at least three of the five dimensions that we use for the provisional identification of the frames (health consequences, economic consequences, popular support, interest group support, and ease of implementation).

Preliminary results from an analysis of thirteen American newspapers shows that media coverage intensifies when major legislation and illustrates how it prioritizes different consequences of smoking bans, such health, economic fallout for businesses, and enforcement issues.

2 Frames as indicators of policy diffusion

We define policy diffusion in terms of interdependence. That is, we consider that policy diffusion occurs if the policy choices of one unit (such as countries, states, cities, etc.) are influenced by the policy choices of other units (Dobbin, Simmons and Garrett, 2007; Gilardi, 2012). Diffusion processes are driven by three broad classes of mechanisms: competition, learning, and emulation (Simmons, Dobbin and Garrett, 2006; Braun and Gilardi, 2006; Dobbin, Simmons and Garrett, 2007; Gilardi, 2012). First, competition means that a unit reacts to the policies of other units in an attempt to attract resources. Second, learning means that the experience of other units is used to estimate the consequences of policy choices. Third, emulation is the idea that the socially constructed properties of policies and their relationship with dominant norms, instead of their objective characteristics, drive policy diffusion. Thus, some policies may become accepted as appropriate regardless of their actual

¹See, for example, “Das Tessin – Vorreiter gegen das Rauchen. Ein Blick über die Grenze” (*Neue Zürcher Zeitung*, 12.10.2005); “Ratsmehrheit für Rauchverbot in öffentlichen Gebäuden. Die Befürworter des Verbots zogen im Kantonsrat Beispiele aus dem In- und Ausland bei, um zu klagen, wie rückständig der Kanton Zürich bezüglich des Schutzes der Nichtraucher sei” (*Neue Zürcher Zeitung*, 21.3.2006); “Wetteifern beim Nichtraucherschutz. Nach der Abstimmung in Solothurn – weitere Kantone planen Gesetzesänderungen” (*Neue Zürcher Zeitung*, 29.11.2006).

consequences. Emulation can also be seen as a process in which the “burden of proof” shifts from the proponents to the opponents of the policy. When a policy is new or heterodox, its proponents must fight against prevailing norms. However, as the policy becomes more accepted, opponents of the policy (that is, defenders of the status quo) are under greater pressure to make their case.

The fundamental idea on which this paper is based is that the frames used in public discourses can be used as indicators of diffusion. Frames can be defined as patterns of justifications linking specific policies with certain beliefs (Entman, 1993; Helbling, Hoeglenger and Wuest, 2010). Empirically, they can be measured through the words, images, and phrases used when conveying information about a policy (Gamson and Modigliani, 1989). Frames inform us on how a given policy is perceived in a given unit. This perception changes as a function of the policy being adopted elsewhere, thereby informing us on the nature of the diffusion process. Regardless of whether the media reflect or influence how policies are framed in public debates, they can be used as an accurate source for ways in which smoking bans are perceived in a given unit—and, crucially, how this perception changes as a function of the adoption of smoking bans in other units.

In our context, frames allow us to identify patterns of justifications that link smoking bans with certain expectations about their effectiveness or appropriateness. As with any other issue, smoking bans allow for a variety of competing frames (Chong and Druckman, 2007, 112–115). Although most of the existing literature on the media coverage of smoking bans tends to focus on tobacco-related news in general or on specific medical issues such as the health consequences of passive smoking, it provides some useful guidelines for the development of our classification (Champion and Chapman, 2005; Nelson et al., 2007; Smith et al., 2008; Foster et al., 2012; Champion and Chapman, 2005). In particular, Champion and Chapman (2005, 680) identify frames related to health, economics, public opinion, or practical arguments and distinguish positive, neutral, and negative tones. Building on these insights, we provisionally identified six frames:

1. *Health consequences*: Are smoking bans considered to have positive, negative, or no effects on the health of the employees of businesses subject to the bans or on the health of the general population?
2. *Economic consequences*: Are smoking bans considered to have positive, negative, or no effects on businesses subject to the ban?
3. *Popular support*: Are smoking bans considered to elicit high or low support among the electorate?

4. *Interest group support*: Are smoking bans considered to elicit high or low support among interest groups?
5. *Implementation*: Is the implementation of smoking bans considered easy or difficult?
6. *Political consequences*: Do smoking bans have positive or negative consequences for politicians?

Table 1 shows four excerpts from newspaper articles that can be linked to the frames defined above. Excerpt A contains the frame “health consequences,” excerpts B and C exemplify the frame “economic consequences,” and excerpt D illustrates the frame “implementation.” We elaborate on these examples below.

We use these frames in three steps. First, we identify the frames empirically and look descriptively at their distribution, both cross-sectionally and over time. Second, we analyze frames as a function of policy adoption in other units. Third, we analyze policy adoption as a function of frames. In this paper, we concentrate on the first step only.

First step: Variation of frames across units and over time. In this step, we identify the frames empirically and examine descriptively their variations across units and over time. This allows us to establish, for instance, which frames are most used, whether their “mix” (for instance, the ratio of different frames or another composite measure) varies over time, whether the frames used focus less on economic consequences over time, and whether states/cantons used the same frames found in similar cantons/states.

Second step: Frames as a function of policy adoption in other units. There are two ways in which the frames can be connected with the process by which policies diffuse. First, we can examine whether a given frame is used with explicit reference to a given unit. For instance, we would interpret excerpt C in Table 1 as indicative of learning from Italy with respect to the economic consequences of smoking bans because the text makes an explicit connection between the experience of another unit (Italy) and a consequence of the policy, namely, positive effects on restaurants. Similarly, excerpt B shows that the economic effects of smoking bans in Delaware were used to estimate the likely consequences of the policy in New Jersey. Excerpt D also includes explicit information on the likely consequences of the policy based on the Italian experience but this time with reference to their implementation. On the other hand, excerpt A contains less information because, although other units are mentioned, there is no explicit connection between the frame and those units. Thus, based on excerpt A, we cannot

- A North Carolina, the nation's largest grower of tobacco, will soon prohibit smoking in restaurants and bars. The ban, signed into law on Tuesday by Gov. Bev Perdue, is another defeat for the ailing tobacco industry on home turf in the South. [...] "This is a historic day for North Carolina," said Governor Perdue, a Democrat. "By banning smoking in our restaurants and bars, we will greatly reduce the dangers of secondhand smoke and lower health care costs for families." [...] Since March, smoking has been banned in most bars and restaurants in Virginia, where tobacco has been grown for 400 years.
(*New York Times*, 19.5.2009)
- B Several recent studies support the casino owners' fears that they will lose business. An analysis of the Delaware smoking ban by Richard Thalheimer, an authority on the horse racing industry and casino gambling who teaches at the University of Louisville, found that the ban was followed by reductions of 11 to 19 percent in slot machine wagering at racetracks. [...] Another study, commissioned last year by the Casino Association of New Jersey, a trade group, and using Delaware as a baseline, estimated that a ban in Atlantic City would depress annual gambling revenue, now about \$5 billion, by about \$1 billion after two years.
(*New York Times*, 29.11.2006)
- C The fears of bar and restaurant owners that earnings would be drastically reduced if smoking were no longer allowed in their establishments have proved to be unjustified. On the contrary: in Italy, it seems that more people are going to restaurants since the smoking ban entered into force than before.
Befürchtungen von Wirten und Barbetreibern, die Einnahmen würden drastisch zurückgehen, wenn in ihren Lokalen nicht mehr geraucht werden darf, haben sich als unbegründet erwiesen. Im Gegenteil: In Italien scheinen seit Inkrafttreten des Rauchverbots eher mehr Leute in Restaurants zu gehen als vorher.
(*Neue Zürcher Zeitung*, 12.10.2005)
- D The everyday life of Italians is regulated by an enormous number of laws—at least in theory, because their implementation is usually very weak. However, in the case of smoking bans, citizens have accepted the new rules with some initial skepticism, but they respect them astoundingly well.
Der Alltag der Italiener wird von einer riesigen Zahl von Gesetzen geregelt—theoretisch zumindest, denn mit der Durchsetzung hapert es in der Regel beträchtlich. Im Falle des Rauchverbotes allerdings unterzogen sich die Bürger den neuen Bestimmungen anfänglich vielleicht murrend, doch sie halten sich erstaunlicherweise daran.
(*Neue Zürcher Zeitung*, 12.10.2005)

Table 1: Examples of frames found in newspapers (A: health consequences; B and C: economic consequences; D: implementation).

conclude that the experience of other units is taken as evidence of a certain consequence of the policy. Moreover, in this excerpt, there are arguably two frames: The most explicit is “health consequences,” but the reference to tobacco production can be interpreted as a hint about the economic effects of smoking bans. Second, we can examine how the “mix” of frames (for instance, their relative frequency), as well as their tone varies as a function of policy choices in other units. Here, frames are the dependent variable, while the key explanatory variable is the adoption of smoking bans in other units. If the frame “implementation,” for instance, becomes less prevalent or assumes a more positive tone after adoption by other units, then we would consider this to be evidence of diffusion because the perception of a given consequence of the policy changes as a reaction to the experience of others. Moreover, we could examine whether arguments in favor of smoking bans are more frequent than those against them in earlier periods, but the frequency reverses over time. If that is the case, it would suggest that the “burden of proof” shifts from proponents to opponents, which is in line with the idea that some policies may gain widespread acceptance and be internalized as appropriate.

Third step: Policy adoption as a function of frames. The last step involves establishing whether there is a connection between the frames that are used and the adoption of the policy, that is, whether frames influence the likelihood that the policy diffuses to a specific canton/state. Do any of the frames, or their “mix” (such as the ratio of different frames), increase the likelihood of adoption or the speed with which a government adopts the policy? Here, the dependent variable is the adoption of smoking bans, while the key explanatory variable is the frames that are used in a given unit.

3 Methodology

The units of analysis in this study are Swiss cantons and U.S. states. Switzerland and the United States share a strong federal structure in which subnational units retain considerable autonomy in most policy areas, including public health and, specifically, smoking restrictions. In both countries, antismoking policies were first debated and adopted at the subnational level. The advantage of examining these two countries is that they are highly comparable in this specific policy area, making it possible to apply our approach with only minor adaptations while at the same time providing sufficient variation to test its strengths and weaknesses in different contexts. Concerning the time frame, we set the beginning of the observation period two years before the first state/cantonal adoption, namely, 1996 for the United

States (the first statewide smoking ban was adopted in California in 1998)² and 2003 for Switzerland (the first smoking ban was adopted in Ticino in 2005). Moreover, 2003 was also the year in which a nationwide smoking ban was approved in Italy (implemented two years later). As shown by the examples in Table 1, the Italian example definitely had some influence on Swiss debates.

To analyze public debates, we rely on articles published in the newspapers listed in Table 2. We use the print media rather than television or radio programs for technical reasons but also because they report generally more extensively on political matters than do on-air media (Druckman, 2005, 469). We will examine public debates both at the national and regional levels. The national level constitutes an important benchmark for the debate in the subnational units. The focus of the paper, however, is the diffusion of smoking bans among the subnational units. Thus, public debates will be examined primarily at the level of cantons/states.

At the moment, the construction of the software pipeline is not completed yet and the sample of manually annotated documents is restricted to the following newspapers: *Arizona Republic*, *Atlanta Journal*, *Boston Globe*, *Chicago Tribune*, *Daily News*, *Denver Post*, *New York Times*, *Philadelphia Inquirer*, *Seattle Times*, *St. Louis Post-Dispatch*, *Star Tribune Minneapolis*, and *USA Today*. Therefore, our preliminary analysis is limited to the coverage of smoking bans in these newspapers. We used an application programming interface (API) to build a corpus of potentially relevant newspaper articles with the search string “*tobacco OR non-smoking OR anti-smoking OR smoking OR cigar! OR (lung AND cancer) OR smoker*” from 1996 to 2013, which yielded 319,806 documents (see Table A1 for overview of the corpus). After several preprocessing steps (i.e. removing of html markups, punctuations, and unnecessary whitespace characters), we split the articles into paragraphs containing at least 150 words, which produced 1,970,369 paragraphs.

Then, we manually annotated a sample of 12,603 paragraphs. Usually, a much smaller sample of hand-coded documents is necessary (Grimmer and Stewart, 2013). However, in our case, reports on actual smoking bans are very rare. The search string matched a lot of documents which covered smoking in other contexts (e.g. smoking in movies, health problems unrelated to regulation, restaurant reviews mentioning that a restaurant is non-smoking). Consequentially, we had to increase the sample for the manual annotation in order to produce enough relevant paragraphs for the supervised machine learning. We coded three variables for each paragraph: relevance for smoking bans, frame categories,

²Debates on smoking bans go back at least to the introduction of the first smoke-free spaces in the 1980s. The Minnesota Clean Indoor Air Act, for example, called for a partial smoking ban in bars and restaurants as early as 1975. However, the analysis requires significant public debates associated with highly visible events.

	National	Regional
US	Wall Street Journal	Chicago Tribune (East North Central)
	New York Times	Detroit News (East North Central)
	USA Today	Daily News (Middle Atlantic)
		Philadelphia Inquirer (Middle Atlantic)
		Denver Post (Mountain)
		Arizona Republic (Mountain)
		Boston Globe (New England)
		Hartford Courant (New England)
		Los Angeles Times (Pacific)
		Seattle Times/Post-Intelligencer (Pacific)
		Washington Post (South Atlantic)
		Atlanta Journal-Constitution (South Atl.)
		Star Tribune Minneapolis(West North Central)
		St. Louis Post-Dispatch (West North Central)
CH	Neue Zürcher Zeitung (D)	Tagblatt der Stadt Zürich (Zurich, D)
	Le Temps (F)	Tages-Anzeiger (Zurich, D)
	20 Minuten (D)	Aargauer Zeitung (Northwest, D)
	20 Minutes (F)	Basler Zeitung (Northwest, D)
	Blick (D)	Berner Zeitung (Espace Swiss Plateau, D)
		Bund (Espace Swiss Plateau, D)
		Neue Luzerner Zeitung (Central Switzerl., D)
		24 Heures (Lake Geneva Region, F)
		Le Matin (Lake Geneva Region, F)
		Thurgauer Zeitung (Eastern Switzerland, D)
		Südostschweiz (Eastern Switzerland, D)
		Corriere del Ticino (Ticino, I)
		LaRegione Ticino (Ticino, I)

Table 2: Selected sources for the content analysis. Language labels in parentheses: G=German, F=French, I=Italian

and geographic units.

First, we coded whether a paragraph is actually about smoking bans, that is, state or federal regulation of smoking in public places or specific workplaces. This definition includes statements about any kind of restriction of smoking (smoking bans) in public places and/or businesses introduced through legislative action, executive action or other democratic actions (e.g. direct democratic processes). By contrast, paragraphs discussing, for example, smoking bans introduced by private actors (e.g. companies, businesses), or bans of specific tobacco products (e.g. mentholated cigarettes) are irrelevant for our purposes and are excluded from the sample.

Second, we coded the presence of the frames described in Section 2. For *popular support*, we considered statements that smoking bans are popular or unpopular among the public, or that public opinion is in favor of or opposed to smoking bans. For *interest group support*, we considered statements that smoking bans are supported or opposed by interest groups such as the tobacco industry or professionals such as health care officials or doctors. For *economic consequences for businesses*, we considered statements that smoking bans have positive or negative effects on businesses affected by the ban, such as an increase or decrease of profits or customers, as well as renovation or restructuring costs induced by the introduction of smoking bans and statements about general economic effects of smoking bans. For *implementation/enforcement*, we considered statements of the ease or complexity of the implementation processes, implementation costs, transition periods, special arrangements or exceptions, level of compliance, as well as of social effects of smoking bans. For *health consequences*, we considered statements that smoking bans reduce (or, less likely, increase) dangers from secondhand smoking and tobacco-related illnesses, that they protect people from secondhand smoking, and that they reduce health care costs. Finally, for *political consequences*, we considered statements that politicians supporting or opposing smoking bans should expect increasing or decreasing support among voters, that smoking bans are supported or opposed by specific parties or members of specific parties or groups (e.g. doctors, tobacco industry), that support for smoking bans increases or decreases party or candidate funding, or that smoking bans affect the relationship between the tobacco industry and political figures, groups or parties.

Third, in order to capture the diffusion of smoking bans across units, it is important to identify the units mentioned in the paragraphs. Consequently, we have coded whether a paragraph mentions smoking bans in a particular unit (e.g. the paragraph discusses smoking bans in Wisconsin) or a unit as

a source for the introduction of the policy elsewhere.

On the basis of this manual annotation, we then applied and evaluated supervised computational linguistic methods to label the remaining paragraphs in the corpus. First, we set up a machine learning environment which allowed the systematic comparison of various text processing and classifier parameters for the selection of relevant paragraphs. As for the text processing, we varied several information reduction techniques, i.e. the exclusion of stopwords,³ short words, numbers and words according to their part of speech,⁴ lowercase transformation and lemmatization.⁵

For the classification parameters, we evaluated a maximum entropy (*maxent*) classifier against several alternative options such as support vector machines and *glmnet* (Jurka, 2012) as well as different weighting procedures (term frequencies with or without inverse document frequencies). The text processing and classifying parameters were combined to 384 classification runs, which were systematically evaluated in terms of their reliability. We trained the classifier on 80% of the manually annotated paragraphs and tested it for F-score, recall, and precision⁶ on the remaining 20% of paragraphs. Moreover, since the manual annotation yielded about 40 times more irrelevant paragraphs, we were able to cross-validate all classification runs by comparing 40 samples of irrelevant paragraphs against the set of relevant ones.

The best classifier used the following parameters: no lemmatization, numbers and words with less than 2 characters not excluded, exclusion of stopwords as well as all words except verbs, nouns, and adjectives, lowercase transformation, term frequency weighting without inverse document frequency weights and a *maxent* algorithm. Table 3 shows the reliability measures for this classifier. It achieved an F-score of 0.89 for the separation of the paragraphs into relevant and non-relevant ones, a number which can compete well with interannotator agreement levels that are usually achieved in manual annotations. Furthermore, the error rate is well-balanced both in terms of recall (0.89) and precision (0.90) as well as the recognition of irrelevant (0.91) and relevant (0.88) paragraphs separately. Thus, we are confident that our estimations reveal the general trend in the newspapers' coverage of smoking bans, especially since most tested classification runs agreed with an F-Score of 0.8 or higher—a further sign for the consistency and thus reliability of the classification (Collingwood and Wilkerson, 2012).

³Non content-bearing words as defined in the Snowball list (<http://snowball.tartarus.org/algorithms/english/stop.txt>).

⁴We successfully tried the exclusion words which were not tagged as (<http://www.cis.upenn.edu/treebank/>) verbs, nouns, or adjectives. The Penn Treebank tag set was implemented to tag the part of speech of tokens

⁵We applied the TreeTagger (<http://www.ims.uni-stuttgart.de/projekte/corplex/TreeTagger/>) to lemmatize tokens.

⁶The F-score is the harmonized average of the recall (indicating the share of false negatives) and precision (measuring the share of false positives) of a classification.

	<i>F-score</i>	<i>Recall</i>	<i>Precision</i>
Overall	0.893 (0.063)	0.894 (0.087)	0.900 (0.077)
Recognition of irrelevant paragraphs	0.906 (0.050)	0.929 (0.062)	0.889 (0.071)
Recognition of relevant paragraphs	0.880 (0.072)	0.859 (0.095)	0.911 (0.081)

Table 3: *Detection of paragraphs covering smoking bans: Reliability measures for the best classification run on the test set in 40-fold cross-validation (Standard errors in brackets).*

Second, to estimate the relative frequency of frames in each of our units for every year (or quarter), we employed the supervised learning method developed recently by Hopkins and King (2010). The procedure builds on standard preparation of unstructured text documents for supervised learning (Pang, Lee and Vaithyanathan, 2002). All documents are prepared using a set of preprocessing methods, including text segmentation into paragraphs and sentences, tokenizing, removal of punctuation, as well as stemming and converting all words to lowercase (Hopkins and King, 2010). Then, the preprocessed text is summarized by using its word stem profile, a set of dichotomous variables that stand for the presence or absence of a unigram (a single word stem). To correct for the uncertainty of the estimation, the labeled set is divided into training and test sets. After optimizing the training set, its degree of misclassification is used to calculate a correction coefficient to get unbiased estimates for the whole sample. Finally, the proportion of documents in the target population is estimated using a probability function based on direct tabulation from the pattern of word stem profiles in the labeled set (King and Lu, 2008). This makes it possible to estimate proportions of variables of interest—in our case, the frequency of frame polarities (Hopkins and King, 2010).

4 Preliminary results

We present preliminary findings on the coverage of smoking bans in the thirteen newspapers considered so far in our analyses. Our project is still at an early stage and we can provide only descriptive evidence. Table 3 gives an overview of the content analysis in terms of the detection of relevant paragraphs. In the documents we annotated manually, only a small portion of paragraphs was coded as relevant from the supervised classification. However, the share of relevant paragraphs is considerably higher for the automated classification than for the manual annotation (25.7% compared to 2%, see Table A1 in the Appendix). This means that—although the evaluation of the machine learning procedure is very encouraging—the classifier significantly overestimates the number of relevant paragraphs. In future

iterations of the analysis we will monitor potential misclassifications more closely by extending the manually annotated training sample as well as by evaluating qualitatively the selection for false negatives and false positives. Nevertheless, there is reason to believe that our classifier detects the general trends in the coverage of smoking bans.

Based on the supervised identification of relevant paragraphs in the thirteen newspapers, Figure 1 presents a small multiple plot on how the newspapers report on smoking bans over time. The points indicate the number of monthly published paragraphs since 1996; the line and the grey area indicate the loess smoothed trend with its 95% confidence interval, respectively.⁷ If we pool all newspapers (graph in the upper left corner), a clear development over time becomes visible. The coverage of smoking bans soared to around 3000 paragraphs in the late 1990s, reached its peak in 2003 and then gradually decreased to around 1500 towards the end of the research period. In all newspapers except the *Star Tribune* and the *Washington Post* coverage was intense in the period prior to the introduction of statewide smoking bans, peaked when legislation was passed and then decreased. Further, it can be speculated that the peak values in the late 1990s are related to the extension of the smoking bans in California to bars, making California the first US state to enact a complete ban in all enclosed workplaces. Overall, reports on smoking bans in the US spiked again at the end of 2003, which is likely related to the introduction of a statewide smoking ban for all enclosed workplaces in New York, closely followed the very similar Smoke-Free Air Act in New York City. Thus, it is plausible that the US newspapers pay particular attention to the two major successful smoking bans in the last two decades.

Regarding the trends for individual newspapers, we tend to find three distinctive patterns. First, the *Arizona Republic*, *Boston Globe*, *Daily News*, *Star Tribune*, and *Washington Post* all reported most intensely on smoking bans in the context of the implementation of a comprehensive smoking ban either statewide or in the state capital. This holds for the Smoke Free Arizona Act in 2007 and the *Arizona Republic*, the Boston Clear Indoor Air Regulation in 2003 and the *Boston Globe*, the New York State Public Health Law 1399-O in 2003 and the *Daily News*, the Non-smoking ordinance in Minneapolis in 2005 and the *Star Tribune*, and the Smoking in Public Places Law in Washington DC in 2005 and the *Washington Post*. Second, the attention of the *Chicago Tribune*, the *Denver Post* and the *Philadelphia Inquirer* seemed to have peaked when smoking bans were considered in the state capitals where they are headquartered. In all three cities, we found evidence of a major public debate on smoking bans, the respective legislation, however, was never enforced due to political resistance. Finally, some newspapers

⁷The development of the number of relevant articles over time (not shown) is very similar to the trends in Figure 1.

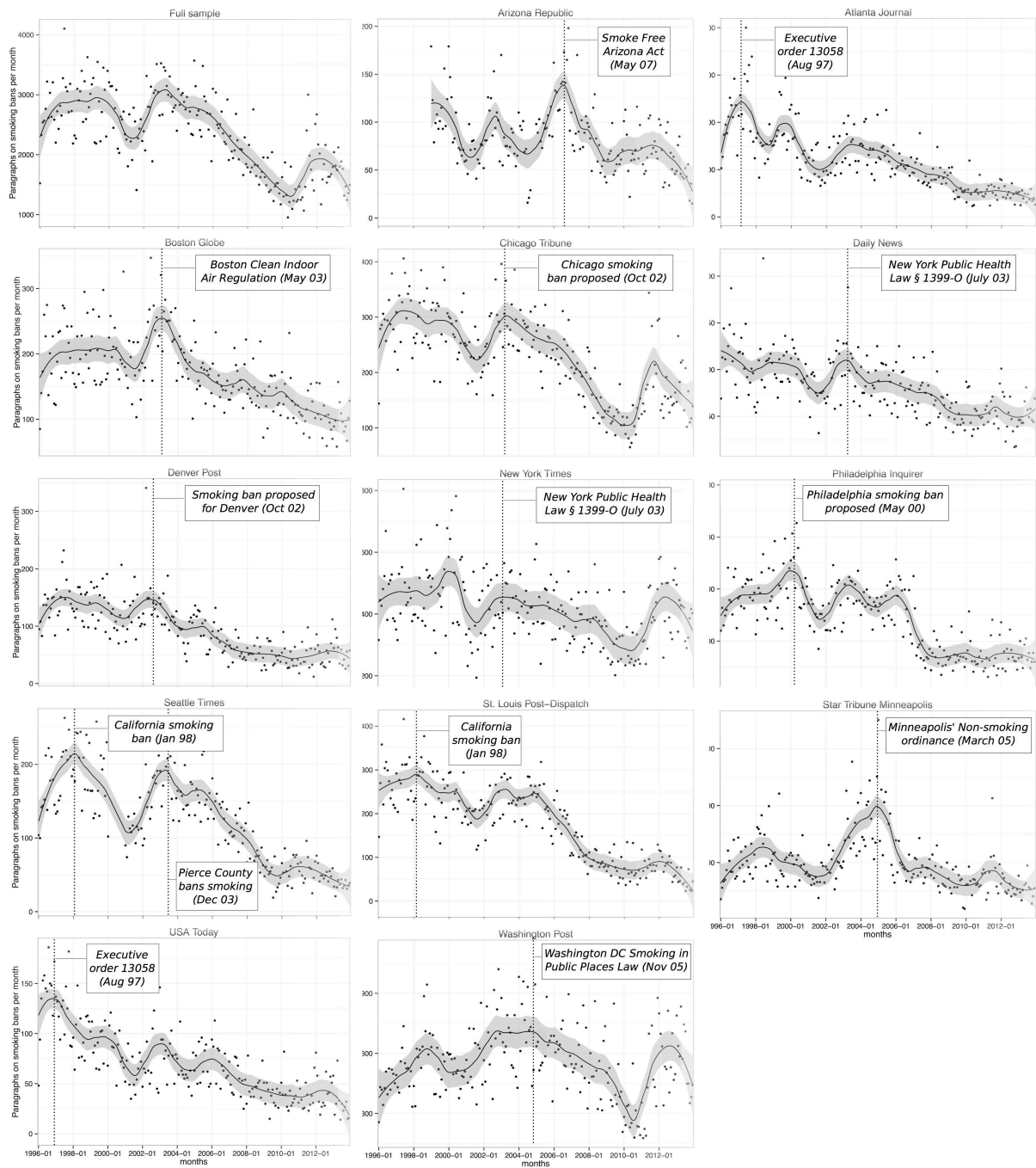


Figure 1: Coverage of smoking bans in US newspapers

seem to react mostly to nationally important events. On the one hand, the *Atlanta Journal* and *USA Today* followed smoking ban legislation most intensely when President Clinton signed a smoking ban in all federal workplaces in 1997 into law. On the other hand, the statewide ban in California seem to have influenced reporting in the *Seattle Times* and *St. Louis Post-Dispatch*. The *New York Times* is the only case where the trend does not seem to reflect major legislative activity. Although the first cities and counties in the State of New York enacted smoking bans in early 2000, this seems not likely to be consequential to the peak in the *New York Times*' coverage of smoking bans.

In general, it is encouraging for the validity of our supervised classification that the development of US newspapers' coverage on smoking bans seems to mirror the proposition, debate, and introduction of major legislative acts. With a newspaper sample that covers all geographical regions in the US, we are therefore confident to collect data on all major legislative activity related to smoking bans. However, we have only presented very tentative evidence on the feasibility of our method to detect relevant smoking ban paragraphs, which is why we will heavily invest in the validation of our recognition in the near future.

Figure 2–7 present small multiple plots with first results on the recognition of frame polarities for the six frames discussed in the theoretical sections (popular support, interest group support, economic consequences for businesses, implementation/enforcement, health consequences, political consequences).⁸ The share of three polarities (positive, neutral/ambivalent, and negative) is presented along with a loess smoothed trend line and confidence intervals in order to show the general trends more clearly. Frame polarities, in turn, are defined as the connotation of the frame in terms of the consequences of smoking ban. Thus, the analyses show if, and when, a frame is more intensely used in relation to a specific consequence of smoking bans.

It is not surprising that health consequences are most often perceived to improve as a consequence of smoking bans (Figure 2). However, the importance of positive health frames declines in the estimations in both the pooled sample as well as in most individual newspapers. The share of frames on health consequences with a neutral or negative polarity increases considerably over time. The increase in ambivalent health frames can most clearly be observed for the coverage of the *Arizona Republic*, *Boston Globe*, *Denver Post*, *New York Times*, *Philadelphia Inquirer*, and *Washington Post*. The increase of negative health frames is strongest for the *Atlanta Journal*, *Philadelphia Inquirer*, *Seattle Times*, *St. Louis-Dispatch*

⁸To add a note of caution: these analyses are have to be regarded as presenting very tentative evidence, since we so far did not conduct extensive reliability or validity checks.

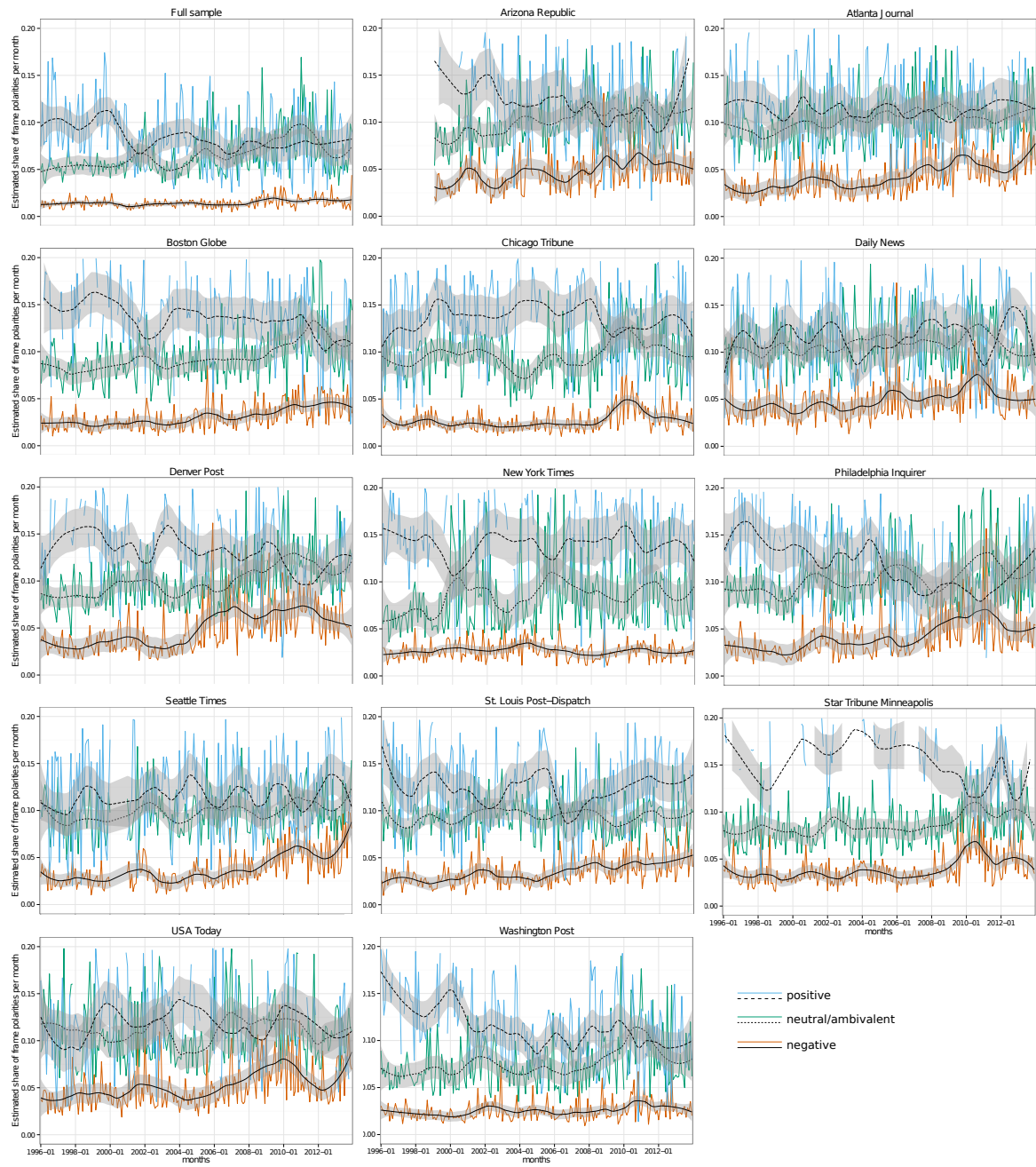


Figure 2: *How smoking bans are framed in terms of health consequences*

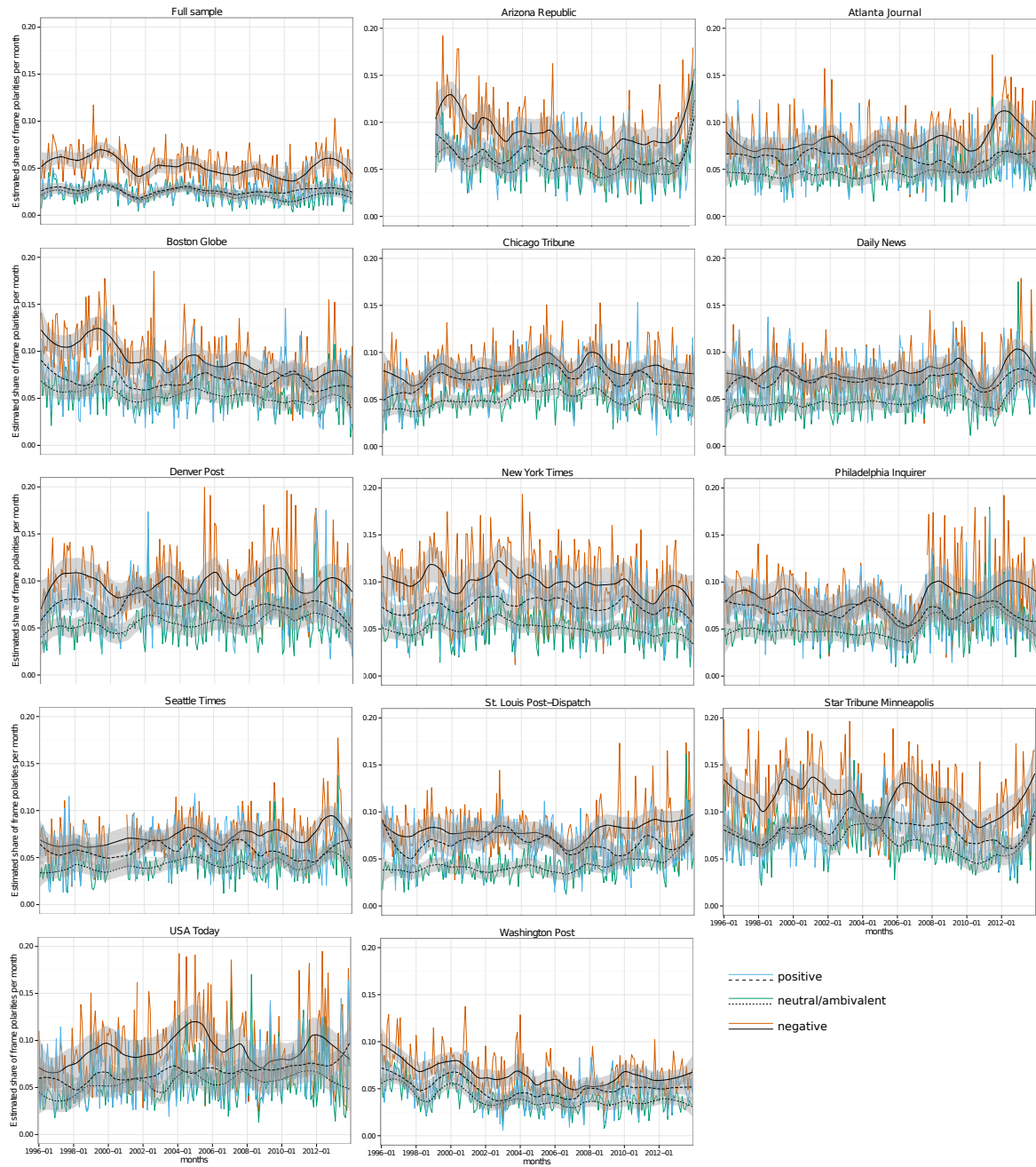


Figure 3: *How smoking bans are framed in terms of economic consequences*

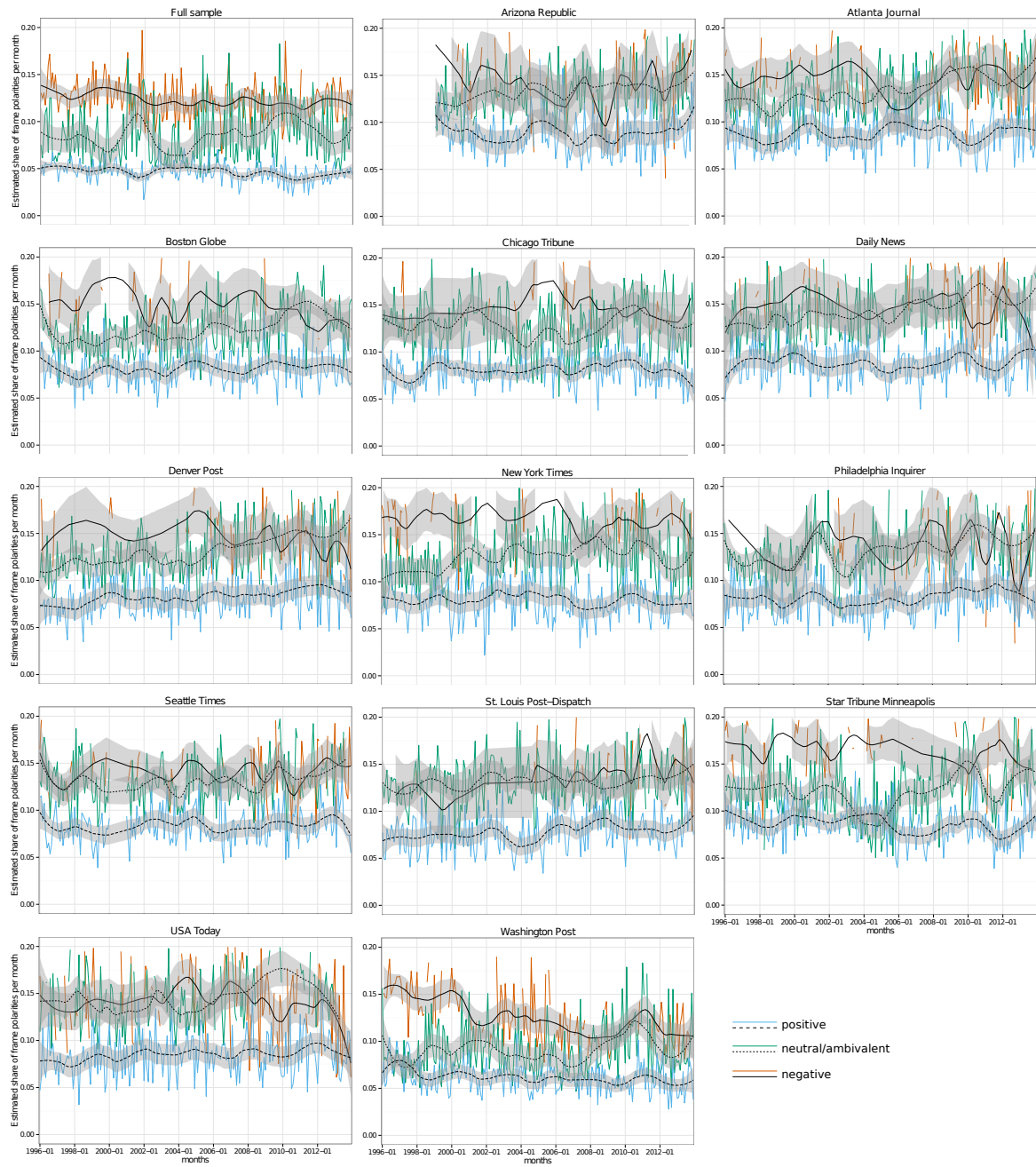


Figure 4: *How smoking bans are framed in terms of implementation considerations*

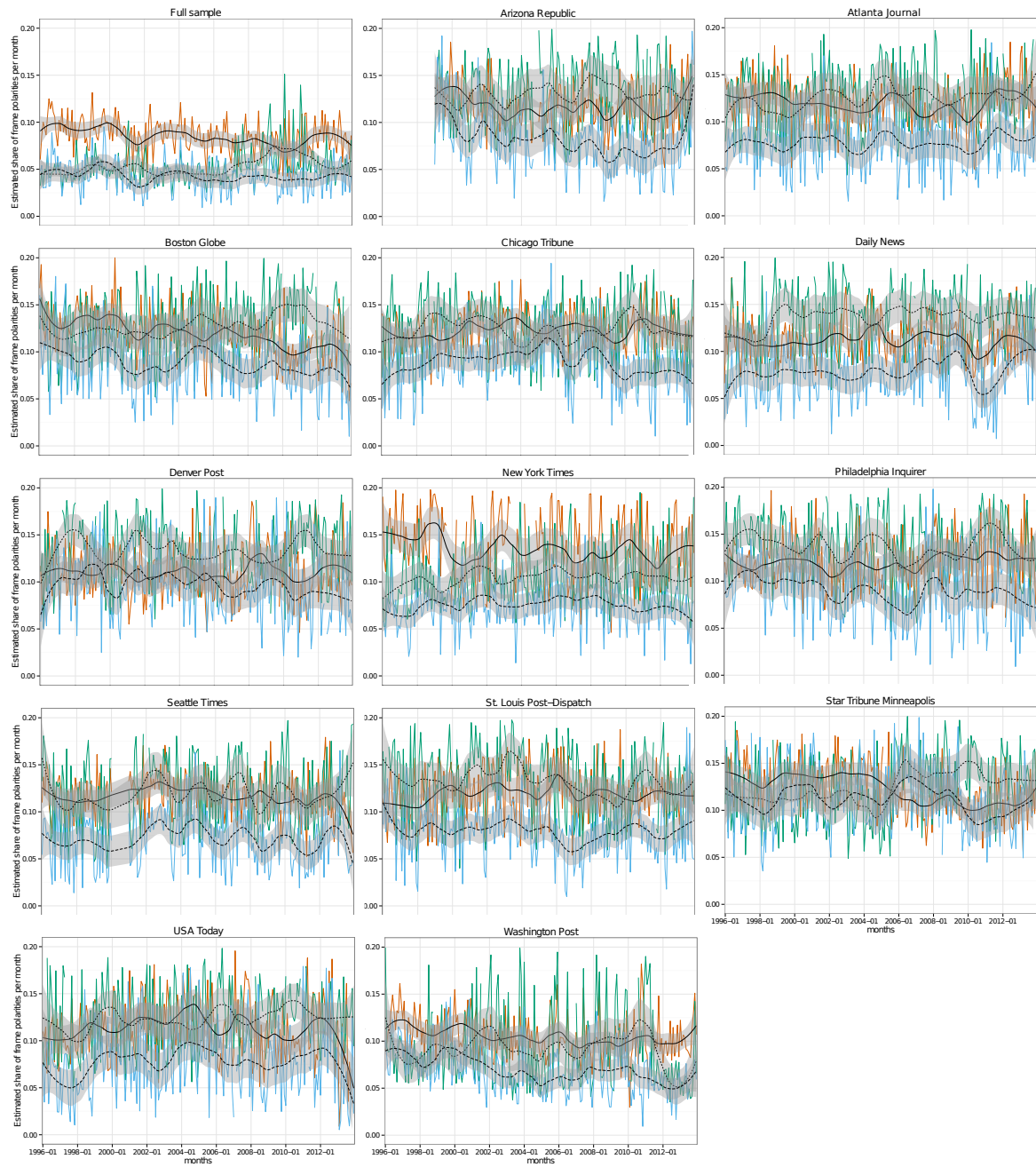


Figure 5: *How smoking bans are framed in terms of interest group pressure*

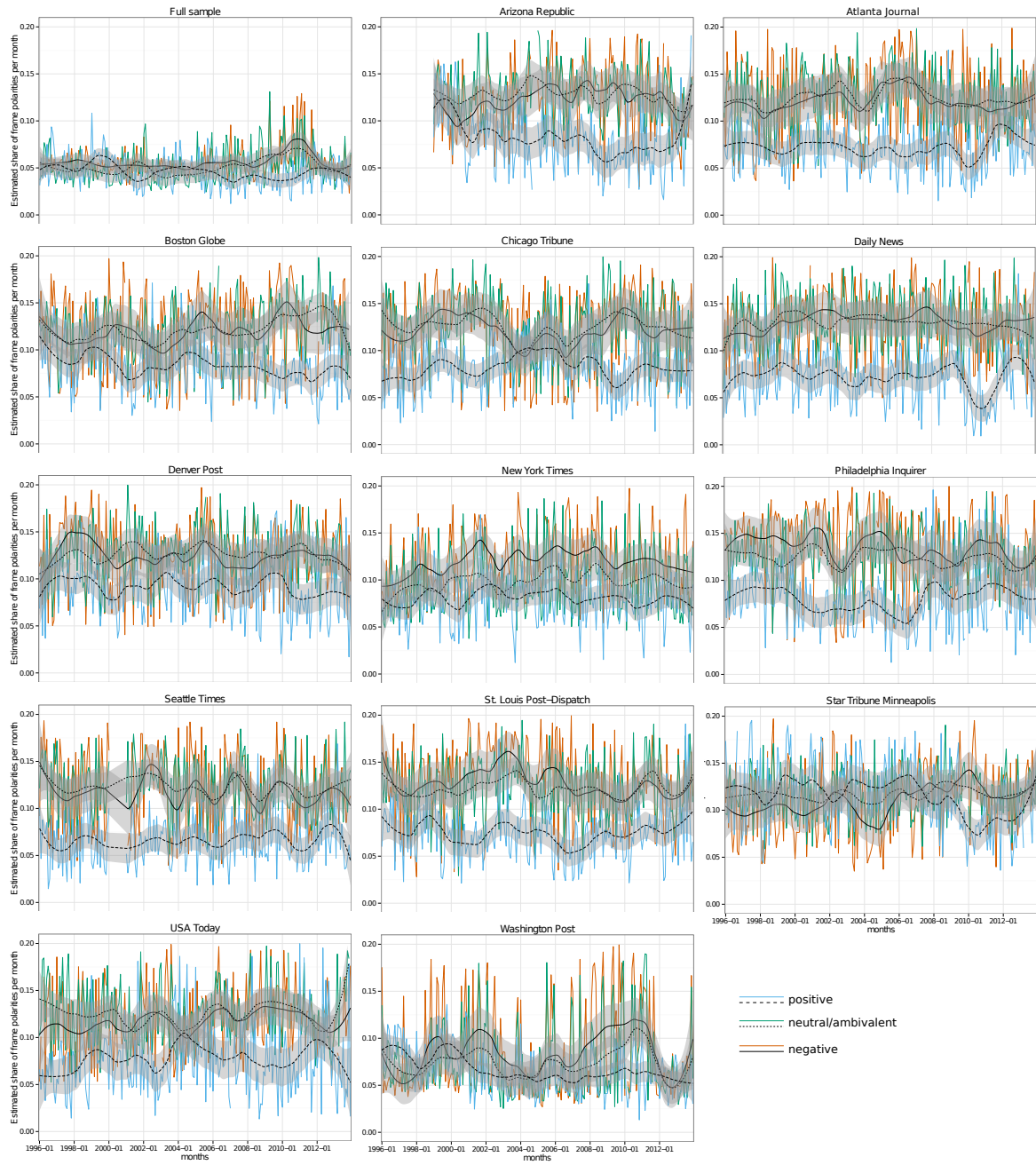


Figure 6: *How smoking bans are framed in terms of popular support*



Figure 7: *How smoking bans are framed in terms of political consequences*

and *USA Today*. The experience from the manual annotation suggests that these developments are most likely related to the increase in smoking ban regulations. In the beginning, every additional smoking ban was seen as an improvement. However, with more and more legislation enacted, coverage became more critical and often proposed smoking bans are not seen as far-reaching enough.

The economic consequences frame is shown in Figure 3. In the coverage of almost all newspapers and throughout the research period, arguments regarding the effects of smoking bans on businesses are negatively connotated. The data analysis is too preliminary to go into the details of the single trends, but some few interesting relationships to the policy making process can already be observed. In the context of the comprehensive smoking ban in workplaces, bars, and restaurants in Minneapolis in 2005, for instance, the *Star Tribune* brought forward significantly less negative economic consequences frames.

Interest group pressure and implementation considerations (Figure 5 and 4) also seem to be frames that are more often characterized by negative polarity, but the patterns are less clear. The overall trends, however, show an interesting development. Towards 2010, the dominance of negative frames is eroding, and more neutrally connotated frames are used. This probably points to a decreasing influence of these arguments in the public debate on smoking bans. At the same time, this speculation cannot be confirmed by the estimations for the individual newspapers and it has to be taken with a grain of salt. Popular support and political consequences frames, finally, are less important than the other frames (Figure 6 and 7). The polarities with respect to these two frames only reach a share of 5 percent or less in the full sample throughout the research period. In addition, the differences between the negative, neutral/ambivalent and positive polarities are not showing distinct patterns on how these frames are used in the coverage of smoking bans. However, it is worth mentioning that the manual annotation did not yield many occurrences of these frames in the first place. It is thus possible that there are important differences, but we so far lack the training data to make them clearer.

5 Conclusion

Our project puts forward a new approach for the study of policy diffusion based on statistical methods for automated content analysis. The main idea is to identify how a policy is perceived and how the perception changes as a function of adoption in other units. The results from a preliminary analysis of thirteen American newspapers for the case of smoking bans shows that this newspaper's coverage

of the policy followed legislative activity. Moreover, the results how the relevance of different frames, as well as their polarity, has changed over time. Health is an important frame that has lost some relevance in recent years. The economic consequences of smoking bans are viewed quite consistently with skepticism. Implementation and enforcement issues had initially a negative polarity, which has become slightly more neutral. Similarly, smoking bans were initially seen to elicit negative responses from smoking bans, but the negative polarity has somewhat attenuated over time. Finally, political consequences and popular support are marginal frames.

In addition to refining the measurement of frames, the next step will be to connect variations in frames with diffusion, that is, to see how frames in one states are influenced by the policies of other states.

References

- Boehmke, Frederick J. 2009. "Policy Emulation or Policy Convergence? Potential Ambiguities in the Dyadic Event History Approach to State Policy Emulation." *Journal of Politics* 71(3):1125–1140.
- Braun, Dietmar and Fabrizio Gilardi. 2006. "Taking 'Galton's Problem' Seriously: Towards a Theory of Policy Diffusion." *Journal of Theoretical Politics* 18(3):298–322.
- Champion, David and Simon Chapman. 2005. "Framing pub smoking bans: an analysis of Australian print news media coverage, March 1996–March 2003." *Journal of Epidemiology and Community Health* 59(8):679–684.
- Chong, Dennis and James N. Druckman. 2007. "Framing Theory." *Annual Review of Political Science* 10(1):103–126.
- Collingwood, Loren and John Wilkerson. 2012. "Tradeoffs in Accuracy and Efficiency in Supervised Learning Methods." *Journal of Information Technology & Politics* 9(3):298–318.
- Dobbin, Frank, Beth Simmons and Geoffrey Garrett. 2007. "The Global Diffusion of Public Policies: Social Construction, Coercion, Competition, or Learning?" *Annual Review of Sociology* 33:449–472.
- Druckman, J. N. 2005. "Media Matter: How Newspapers and Television News Cover Campaigns and Influence Voters." *Political Communication* 22(4):463–481.
- Entman, R. M. 1993. "Framing: Toward Clarification of a Fractured Paradigm." *Journal of Communication* 43(4):51–58.
- Foster, Caroline D, James F Thrasher, Sei-Hill Kim, John C Besley and Ashley Navarro. 2012. "Agenda-Building Influences on the News Media's Coverage of the US Food and Drug Administration's Push to Regulate Tobacco, 1993-2009." *Journal of Health and Human Services Administration* 35(3):303.
- Franzese, Robert J. and Jude C. Hays. 2007. "Spatial Econometric Models of Cross-Sectional Interdependence in Political Science Panel and Time-Series-Cross-Section Data." *Political Analysis* 15(2):140–164.
- Gamson, William A and Andre Modigliani. 1989. "Media discourse and public opinion on nuclear power: A constructionist approach." *American Journal of Sociology* pp. 1–37.
- Gilardi, Fabrizio. 2012. Transnational Diffusion: Norms, Ideas, and Policies. In *Handbook of International Relations*, ed. Walter Carlsnaes, Thomas Risse and Beth Simmons. Second ed. SAGE Publications pp. 453–477.
- Gilardi, Fabrizio and Katharina Füglistner. 2008. "Empirical Modeling of Policy Diffusion in Federal States: The Dyadic Approach." *Swiss Political Science Review* 14(3):413–450.

- Graham, Erin R., Charles R. Shipan and Craig Volden. 2013. "The Diffusion of Policy Diffusion Research in Political Science." *British Journal of Political Science* 43(3):673–701.
- Grimmer, Justin and Brandon M Stewart. 2013. "Text as data: The promise and pitfalls of automatic content analysis methods for political texts." *Political Analysis* .
- Helbling, M., D. Hoeglenger and B. Wueest. 2010. "How Political Parties Frame European Integration." *European Journal of Political Research* 49(4):495–521.
- Hopkins, Daniel J. and Gary King. 2010. "A Method of Automated Nonparametric Content Analysis for Social Science." *American Journal of Political Science* 54(1):229–247.
- Jurka, Timothy P. 2012. "maxent: An R Package for Low-memory Multinomial Logistic Regression with Support for Semi-automated Text Classification." *R Journal* 4(1).
- King, Gary and Y. Lu. 2008. "Verbal Autopsy Methods with Multiple Causes of Death." *Statistical Science* 23(1):78–91.
- Maggetti, Martino and Fabrizio Gilardi. 2014. "Problems (and Solutions) in the Measurement of Policy Diffusion Mechanisms." University of Zurich.
- Nelson, David E, W Douglas Evans, Linda L Pederson, Stephen Babb, Joel London, Jeffrey McKenna et al. 2007. "A national surveillance system for tracking tobacco news stories." *American Journal of Preventive Medicine* 32(1):79.
- Pacheco, Julianna. 2012. "The Social Contagion Model: Exploring the Role of Public Opinion on the Diffusion of Antismoking Legislation across the American States." *Journal of Politics* 74(1):187–202.
- Pang, B., L. Lee and S. Vaithyanathan. 2002. *Thumbs Up? Sentiment Classification Using Machine Learning Techniques*. Philadelphia, PA: Proceedings of the Conference on Empirical Methods in Natural Language Processing.
- Shipan, Charles R. and Craig Volden. 2006. "Bottom-Up Federalism: The Diffusion of Antismoking Policies from U.S. Cities to States." *American Journal of Political Science* 50(4):825–843.
- Shipan, Charles R. and Craig Volden. 2008. "The Mechanisms of Policy Diffusion." *American Journal of Political Science* 52(4):840–857.
- Simmons, Beth, Frank Dobbin and Geoffrey Garrett. 2006. "Introduction: The International Diffusion of Liberalism." *International Organization* 60(4):781–810.

Smith, Katherine Clegg, Catherine Siebel, Luu Pham, Juhee Cho, Rachel Friedman Singer, Frank Joseph Chaloupka, Michael Griswold, Melanie Wakefield et al. 2008. "News on tobacco and public attitudes toward smokefree air policies in the United States." *Health Policy* 86(1):42.

Appendix

A1 Corpus

Newspaper	<i>Corpus</i>		<i>Annotation</i>		<i>Classifier</i>
	Articles	Paragraphs	Annotated	Relevant	Relevant
Arizona Republic	11'493	57'484	216	14	14'766
Atlanta Journal-Constitution	23'292	129'790	486	6	25'790
Boston Globe	22'558	142'297	533	20	36'566
Chicago Tribune	38'454	88'850	333	16	49'714
Daily News	14'203	72'380	271	6	17'588
Denver Post	12'621	82'286	308	9	20'287
New York Times	53'637	358'881	6'569	85	89'827
Philadelphia Inquirer	18'515	117'957	441	15	30'711
Seattle Times	16'821	100'468	376	8	25'234
St. Louis Post-Dispatch	26'880	154'582	350	12	38'413
Star Tribune	13'099	93'622	579	36	21'545
USA Today	10'913	66'708	250	7	15'144
Washington Post	57'320	505'064	1'891	22	120'805
Total	319'806	1'970'369	12'603	256	506'389

Table A1: *Corpus of articles and paragraphs covering smoking bans: results of manual annotation and maximum entropy classifier.*